Available online at http://icsejournal.com/index.php/JCSE
Journal of Computer Science an Engineering (JCSE)
e-ISSN 2721-0251
Vol. 5, No. 2, August 2024, pp. 99-114

Accuracy Assessment of Monthly Rainfall Predictions using Seasonal ARIMA and Long Short-Term Memory (LSTM)

Ahmad Aldizar Akbar[1], Yahya Darmawan[1,2*], Arief Wibowo[3], Hayatul Khairul Rahmat[1]

[1] Disaster Management Department, University of Budi Luhur, Jakarta, Indonesia
[2] Climatology Department, Indonesia College of Meteorology Climatology and Geophysics (STMKG), Tangerang, Indonesia
[3] Information System Department, University of Budi Luhur, Jakarta, Indonesia
[1] 2234500060@student.budiluhur.ac.id; [1,2] yahya.darmawan@bmkg.go.id*; [3] arief.wibowo@budiluhur.ac.id;
[1] hayatul.khairulrahmat@budiluhur.ac.id
*corresponding author

ARTICLE INFO

Article History:
Received June 17, 2024
Revised July 17, 2024
Accepted August 01, 2024

Keywords:
SARIMA
LSTM
Machine Learning
Rainfall Data
Accuracy

Correspondence:
Email: yahya.darmawan@bmkg.go.id

ABSTRACT

Hydro meteorological disasters are common in Indonesia. Rainfall predictions can help mitigate the impact of these disasters. This research aims to compare the accuracy of monthly rainfall prediction models using Seasonal Autoregressive Integrated Moving Average (SARIMA) and Long Short-Term Memory (LSTM) methods. The input data consists of monthly rainfall records from four locations: Sampali, Kualanamu, Belawan, and Tuntungan, located around Medan, North Sumatra. The dataset spans from 2000 to 2020, with training data from 2000 to 2018 and test data from 2019 to 2020. The accuracy assessment reveals that Belawan has the largest RMSE values for both models, measuring 27.68 mm for LSTM and 28.36 mm for SARIMA. Belawan records the highest MAE values, with LSTM and SARIMA yielding 5.65 mm and 5.79 mm, respectively. SARIMA models effectively capture general trends and seasonality in linear time series data with clear patterns but struggle with extreme changes or sharp fluctuations due to their reliance on linear relationships. In contrast, LSTMs are effective at modeling complex, non-linear relationships, making them suitable for capturing general trends, seasonal patterns, and more complicated variations in the data. Understanding the characteristics of the data is crucial before applying SARIMA or LSTM models.

1. Introduction

According to data from the National Disaster Management Agency (BNPB) in 2023, Indonesia experienced a significant increase in hydro-meteorological disasters. Hydro-meteorological disasters include floods, landslides, and tornadoes, which often occur in various regions of Indonesia [1];[2];[3]. The main causes of these disasters are high rainfall, climate change, and environmental damage due to deforestation and unplanned urbanization. Considering Indonesia's geographical and tropical climate conditions, the likelihood of hydro-meteorological disasters is very high. Additionally, global climate change, which increases the frequency and intensity of extreme weather, further exacerbates the risk of hydro-meteorological disasters in Indonesia in the future. Therefore, better mitigation and adaptation efforts are needed to reduce the impact of these disasters [4].

Information about rainfall is crucial for mitigation and adaptation needs, especially concerning hydro-meteorological disasters such as floods and landslides [4];[5];[6]. Predicted rainfall data for short periods, such as 1 to 2 years ahead, is essential for effective planning and decision-making. These predictions can be made using statistical or machine learning methods, each of which has its advantages

https://doi.org/10.36596/jcse.v5i2.843

in processing historical weather data and climate trends [7]. Statistical methods can provide a general overview based on past rainfall patterns, while machine learning can process more complex data and produce more accurate predictions by considering various related variables. With accurate rainfall prediction information, governments and communities can prepare mitigation measures such as flood control infrastructure construction, drainage system improvements, and better spatial planning management. Additionally, this information also aids in long-term adaptation by designing strategies to reduce the risk and impact of hydro-meteorological disasters in the future.

Weather forecasting is one solution that can be used to address the issue of data provision. A good forecast should have high accuracy and precision. Various methods have been developed and refined for predicting rainfall, each with distinct strengths and limitations. There are several methods that can be used to predict future rainfall using statistical approaches such as SARIMA and the LSTM algorithm. The Seasonal Autoregressive Integrated Moving Average (SARIMA) model extends the ARIMA model by incorporating seasonal components. ARIMA focuses on past and present values of the dependent variable to generate accurate short-term forecasts but tends to perform poorly over longer periods due to its assumption of stationarity [8]. Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN), have shown considerable promise in time series analysis, including rainfall prediction. LSTM's ability to remember long-term sequences and process large datasets makes it particularly suitable for handling the seasonal and complex nature of rainfall data [9];[10]. The accuracy of monthly rainfall predictions using SARIMA and LSTM varies based on data characteristics. In regions like Indonesia, where complex topography and monsoon-driven climate result in highly variable rainfall patterns, the predictive accuracy of these models can be impacted by the availability of high-resolution historical weather data [11];[12].

Monthly rainfall predictions using LSTM and SARIMA methods have been widely applied to various types of data, including rainfall data. However, the prediction accuracy of monthly rainfall data for both methods can vary depending on the characteristics of the data [11]. Rainfall prediction in Indonesia faces specific challenges due to its complex topography and monsoon-driven climate, which lead to highly variable rainfall patterns. Additionally, the lack of high-resolution historical weather data in many regions of Indonesia can hinder the training and validation of prediction models, impacting their accuracy. This study aims to analyze the accuracy of monthly rainfall predictions using SARIMA and LSTM models in the Medan area and its surroundings. By comparing the models based on accuracy and error metrics, the study seeks to identify the better prediction model to serve as a reference for applications requiring high-quality monthly rainfall data. Accurate predictions support various sectors, including agriculture, urban planning, and disaster management, by providing reliable weather forecasts. The better prediction model, based on accuracy and minimal error, is expected to serve as a reference for various applications that require high-quality monthly rainfall data. Accurate monthly rainfall information can support multiple sectors that depend on weather forecast information.

2. Method

In this study, monthly rainfall data from four rainfall stations around the Medan area in North Sumatra, namely Sampali, Belawan, Kualanamu, and Tuntungan, were collected for the period from 2000 to 2020. The data was obtained from BMKG (Badan Meteorologi Klimatologi dan Geofisika) Regional I Medan, North Sumatra, Indonesia, and can be freely downloaded from https://dataonline.bmkg.go.id/. A total of 240 time series data points were collected for analysis.

https://doi.org/10.36596/jcse.v5i2.843

The collected data was divided into two parts: training and testing datasets. Data from 2000 to 2018 was used as the training dataset, while data from 2019 to 2020 was used as the testing dataset. This division allows for the development of predictive models based on historical rainfall patterns and the assessment of the models' performance on recent data.

In data processing, the SARIMA (Seasonal Autoregressive Integrated Moving Average) and LSTM (Long Short-Term Memory) methods were used to build the rainfall prediction models. SARIMA was chosen for its ability to handle time series data with seasonal patterns, while LSTM was used for its capability to learn long-term dependencies in time series data. After developing the models, accuracy assessment was conducted to evaluate the performance of both methods.

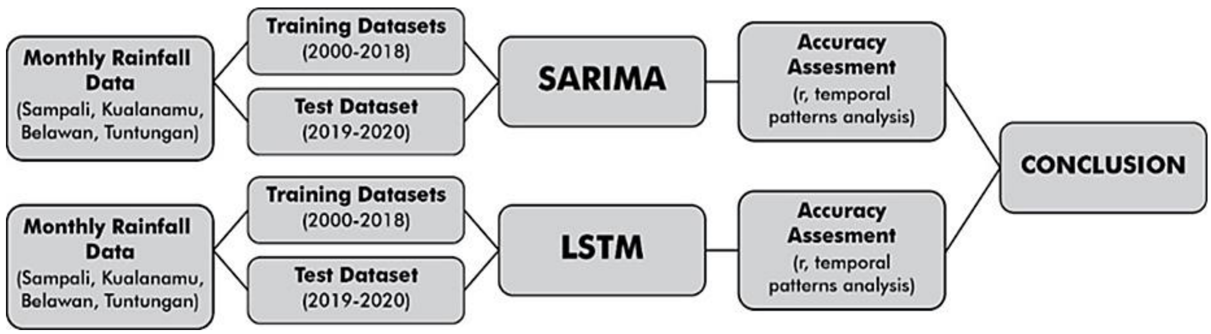

Figure 1. Schematic Flow of Research.

2.1. Data used

Data collection, Monthly rainfall data from four rainfall stations around the Medan area in North Sumatra province were collected, covering the period from 2000 to 2020. The rainfall stations included in the study are Sampali, Belawan, Kualanamu, and Tuntungan. The data was obtained from BMKG (Badan Meteorologi Klimatologi dan Geofisika) Regional I Medan, North Sumatra, Indonesia. Data can be downloaded by free from: https://dataonline.bmkg.go.id/. The total number of time series data is 240 data.

Data preparation, the collected data was divided into training and test datasets. The data from 2000 to 2018 was used as the training dataset, while the data from 2019 to 2020 was used as the test dataset. This division allows for the development of predictive models based on historical rainfall patterns and the assessment of the models' performance on recent data.

2.2. Software used

The research was conducted using several tools for modeling SARIMA and LSTM. The tools used in this study consist of freely downloadable software: Anaconda, provides many pre-installed data science libraries, such as Numpy, Pandas, Matplotlib, and others. Spyder is an Integrated Development Environment (IDE) used for developing Python applications. As an IDE, this application is specifically designed for numerical data analysis and provides various useful tools and features for data scientists and researchers. Microsoft Excel is spreadsheet software used for data analysis and visualization.

In this study, specific parameters were selected for the SARIMA and LSTM models to optimize the accuracy of monthly rainfall predictions. For the SARIMA model, the ARIMA order (p, d, q) was determined using ACF and PACF plots, along with stationarity tests, to effectively capture the autoregressive and moving average components. The seasonal order (P, D, Q, S) was chosen based on

https://doi.org/10.36596/jcse.v5i2.843

the observed seasonal patterns and periodicity in the data, which are essential for accurately modeling seasonal variations in rainfall. Additionally, the AIC/BIC criteria were utilized to select a model that balances fit and complexity, ensuring a parsimonious yet effective model.

For the LSTM model, the number of lagged observations (timesteps) was chosen to capture the temporal dependencies in the data, with domain knowledge and experimentation guiding the optimal number. The number of LSTM units and layers was determined through cross-validation, aiming to balance model complexity and computational efficiency. More units and layers can capture complex patterns but require more data and computational power. The 'relu' activation function and 'Adam' optimizer were selected for their effectiveness in training deep learning models, while the Mean Squared Error (MSE) loss function was used for regression tasks like rainfall prediction, as it penalizes larger errors more significantly. This careful selection of parameters ensures that both the SARIMA and LSTM models are well-tuned to capture the patterns and dependencies in the rainfall data, leading to more accurate and reliable monthly rainfall predictions for the Medan area and its surroundings.

2.2.1. SARIMA

The SARIMA model comprises several components: Autoregressive (AR) term: The AR component indicates the dependency of the current value on previous values in the time series. The number of AR terms is denoted by p , for example, AR(p). Integrated (I) term: The I component indicates the number of differentiations needed to make the data stationary. Differentiation is performed to eliminate trends or seasonal patterns in the data. The number of I terms is denoted by d d, for example, I(d). Moving Average (MA) term: The MA component indicates the dependency between the current value and the residual values (the difference between the current value and the predicted value) in previous periods. The number of MA terms is denoted by q , for example, MA(q).

The SARIMA model adds a seasonal component to each ARIMA component. The ARIMA model is constructed with orders (p, d, q), which is a mixed model of autoregressive (AR) with order p followed by moving average (MA) with order q that undergoes differencing (d) times. Data series plots should assume stationarity. If the data to be processed is not stationary, differencing needs to be performed, and initial values of the d order can be estimated. However, differencing is unnecessary if the data to be processed is already stationary [13][14][15]. ARIMA is a type of short-term prediction model in time series analysis. Due to its systematic and flexible nature, and its ability to capture more original time series information, this method is widely used in meteorology, engineering technology, marine studies, economic statistics, and forecasting technology. Unlike the ARIMA model, the SARIMA model has six components: autoregressive, integrated, moving average, seasonal autoregressive, seasonal integrated, and seasonal moving average [16]. The ARIMA model equation (p,d,q) can be written as follows:

$$Y_t = \xi + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \emptyset_3 Y_{t-3} + \cdots + \emptyset_p Y_{tp} + \varepsilon_{t\ldots} \tag{1}$$

Where :

Yt = stationary series value
ξ = model mean value
$\emptyset_j$ = self-regression model parameters (j = 1, 2, ……., p)
ε_t = normally distributed random error with mean zero and variance σ_2

https://doi.org/10.36596/jcse.v5i2.843

2.2.2. Long Short Term Memory (LSTM)

LSTM is an architecture of RNN (Recurrent Neural Network). LSTM is capable of analyzing, forecasting, and categorizing information that has been stored for a long time [17];[18]. LSTM can be used to process sequential data, thus it can be employed for predicting time series data. LSTM can detect data to be stored and data not to be used for pruning, as LSTM consists of 4 neuron layers commonly referred to as gates to regulate memory in each neuron. Research is conducted by predicting weather data such as rainfall and temperature using the Long Short Term Memory (LSTM) method. The predicted model results can provide suggestions for implementing a good weather prediction model through predictions using the LSTM method [19]. One of the key advantages of LSTM is its ability to remember long-term sequences (data size), which is difficult to achieve with traditional feature techniques. LSTM can handle larger data sizes and utilize all data information as input, thereby constructing a deep network [14]. The first layer is an LSTM layer with a specified number of units, followed by another LSTM layer with its own specified number of units. Dropout is also applied after each LSTM layer to control overfitting. The final layer is an output layer with a single unit activation and a sigmoid function, as this is a binary classification problem [20].

The mathematical calculations in the LSTM model carried out at each stage are given as follows:

$$
\begin{aligned}
&\textit{forget gate}: && \mathbf{f}_t = \sigma(\mathbf{W}_f \mathbf{x}_t + \mathbf{R}_f \mathbf{h}_{t-1} + \mathbf{b}_f) = \sigma(\bar{\mathbf{f}}t) \\
&\textit{input gate}: && \mathbf{i}_t = \sigma(\mathbf{W}_i \mathbf{x}_i + \mathbf{R}_i \mathbf{h}_{t-1} + \mathbf{b}_i) = \sigma(\bar{\mathbf{I}}t) \\
&\textit{candidate state}: && \mathbf{z}_t = \tanh(\mathbf{W}_c \mathbf{x}_c + \mathbf{R}_c \mathbf{h}_{t-1} + \mathbf{b}_c) = \tanh(\bar{\mathbf{z}}t) \\
&\textit{cell state}: && \mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \mathbf{z}_t \\
&\textit{cell gate}: && \mathbf{o}_t = \sigma(\mathbf{W}_o \mathbf{x}_o + \mathbf{R}_o \mathbf{h}_{t-1} + \mathbf{b}_o) = \sigma(\bar{\mathbf{o}}t) \\
&\textit{output}: && \mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t)
\end{aligned}
\tag{2}
$$

Where x_t is the *input vector* at time t, **W** and **R** are *weight matrices.* bt is the bias vector. σ and tanh are activation/transfer functions, and ʘ denotes *element wise multiplication.* [21]provides the detailed algorithm.

2.3. Accuracy Assessment

2.3.1. Root Mean Square Error

Root Mean Square Error (RMSE) is one method used to evaluate forecasting predictions, employed to measure the accuracy level of a model's forecasts. RMSE is the square root of the average of the squared errors and also represents the magnitude of errors produced by a forecasting model [22];[23]. RMSE (Root Mean Square Error) indicates the magnitude of deviation between predicted rainfall values and actual rainfall values. The larger the RMSE value, the greater the discrepancy between the predicted total rainfall and the actual total rainfall. Conversely, the smaller the RMSE value, the better the prediction of total rainfall compared to the actual total rainfall. Minimizing the error level can improve prediction accuracy [24]. RMSE can be expressed with the formula:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi - xi)^2} \tag{3}$$

Where:

RMSE = *Root Mean Square Error*

https://doi.org/10.36596/jcse.v5i2.843

yi = bulk Rain observation
xi = bulk rain model output
n = Number of data

2.3.2. Mean Absolute Error

Mean Absolute Error (MAE) is one method used to measure the accuracy level of a forecasting model. The MAE value indicates the average absolute error between the forecasted/predicted values and the actual values [25];[26]. MAE provides results that can be directly interpreted [27]. It is a commonly used measurement for predicting errors in time series analysis, where the term Mean Absolute Deviation (MAD) is sometimes used interchangeably, referring to the Mean Absolute Error [28]. The larger the MAE (Mean Absolute Error) value, the greater the error in the output, indicating that the model is less optimal in making rainfall predictions [29]. MAE can be explained as follows:

$$MAE = \frac{1}{n}\sum_{i=0}^{n}|fi - yi| \tag{4}$$

Where:

MSE = Mean Absolute Error
fi = value of forecasting results
yi = actual value
n = amount of data

2.3.3. Temporal Pattern Analysis

The objectives of the Temporal Pattern Analysis line graph are multifaceted, aiming to provide a comprehensive understanding of rainfall trends and model performance. Firstly, the graph visualizes temporal trends, helping to identify patterns, seasonality, and anomalies in the rainfall data over time. This allows for a clear illustration of how rainfall fluctuates in each location. Additionally, the graph serves to compare model predictions by plotting the actual rainfall data against the predicted values from both LSTM and SARIMA models. This comparison highlights the accuracy and efficacy of each model in capturing the temporal dynamics of rainfall. Furthermore, the graph aids in evaluating model performance by examining how closely the predicted values align with the actual rainfall over different periods, thus identifying periods where the models underperform or overperform. Anomaly detection is another critical objective, as the graph helps in spotting significant deviations between predicted and actual values, which may indicate model limitations or unique climatic events. Lastly, the graph supports decision-making by offering visual evidence to stakeholders, enabling them to determine which model is more suitable for specific locations based on temporal prediction performance. Overall, the Temporal Pattern Analysis line graph is a valuable tool for understanding, comparing, and enhancing rainfall prediction models.

3. Results and Discussion

3.1 SARIMA

SARIMA determines the model order for each Region automatically. The programming in Python employs the "auto_arima" system for model order selection. Non-seasonal model orders are expressed in lowercase (p,d,q), while seasonal model orders are expressed in uppercase (P,D,Q). The seasonal component is denoted by 's', where 12 represents the number of months in one year. The use of the

https://doi.org/10.36596/jcse.v5i2.843

"auto_arima" function automates the complex task of model selection by testing various combinations of p, d, q, P, D, Q, and s parameters to find the best fit for the given data. This is particularly useful for time series data with strong seasonal patterns, such as monthly rainfall data, where the model needs to account for both short-term fluctuations and annual seasonal effects. Table 1 would provide an example of how these parameters are applied to the rainfall data for each region, demonstrating the specific model orders selected by "auto_arima" for both non-seasonal and seasonal components.

Table 1. Non-seasonal model orders and seasonal model orders of SARIMA for all locations

SARIMA model (p,d,q) (P,D,Q,s)	
Sampali	(1, 0, 0)(2, 0, 0, 12)
Kualanamu	(2, 1, 0)(1, 0, 1, 12)
Belawan	(2, 0, 0)(1, 0, 2, 12)
Tuntungan	(1, 0, 0)(2, 0, 0, 12)

3.2 LSTM

The number and size (number of neurons) of hidden layers in the LSTM algorithm significantly influence the model's ability to capture patterns in sequential data. In this study, the hidden layer structure in the LSTM model is a crucial part of the artificial neural network (ANN) model creation process. The model comprises two hidden layers, each using the Rectified Linear Activation (ReLU) function. ReLU is a popular activation function that deactivates neurons with negative input values and leaves positive input values unchanged, helping to avoid issues like the vanishing gradient problem. The first hidden layer consists of 64 units and uses ReLU as the activation function, with an input shape specified by the look_back parameter. It is implemented in the script as model.add(Dense(64, activation='relu', input_shape=(look_back,))). The second hidden layer consists of 32 units and also uses the ReLU activation function, implemented as model.add(Dense(32, activation='relu')). These hidden layers process the input data with appropriate dimensions to capture underlying patterns without overfitting or underfitting. The Sequential approach is used to build the model, where layers are added one after the other, making the neural network architecture straightforward to construct and understand. By specifying the hidden layers and their respective parameters, the LSTM model is better equipped to process sequential data and uncover intricate patterns in the rainfall data, ultimately leading to more accurate predictions.

3.3 Accuracy Assessment

3.3.1. RMSE

The RMSE comparison graph is plotted on an actual scale (mm). The largest RMSE values for both models are found in Belawan, with 27.68 mm for LSTM and 28.36 mm for SARIMA. In contrast, the smallest RMSE values for LSTM are in Sampali, with 14.45 mm, while the smallest RMSE values for SARIMA are in Tuntungan, with 2.61 mm. This indicates that while LSTM performs better in some locations, SARIMA performs significantly better in others, particularly in Tuntungan (Figure 2).

https://doi.org/10.36596/jcse.v5i2.843

 e-ISSN 2721-0251

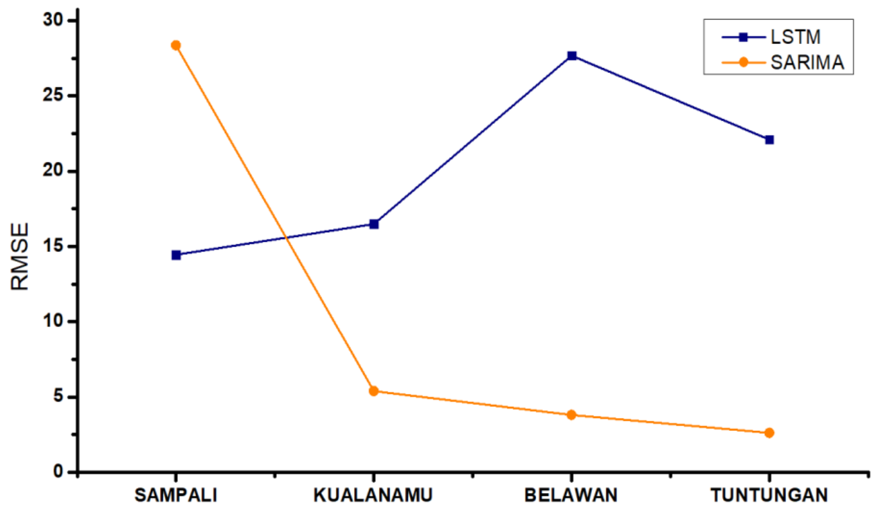

Figure 2. The RMSE Comparison Graph Shows the RMSE Values for LSTM and SARIMA Models Across Four Locations: Sampali, Kualanamu, Belawan, and Tuntungan.

The analysis of the provided RMSE data unveils insights into the performance of LSTM and SARIMA models across different regions. Notably, the comparison highlights distinct strengths and weaknesses of each model. In Belawan, both models exhibit higher RMSE values, indicating challenges in accurately predicting environmental variables in this area. However, in Sampali, the LSTM model showcases better predictive accuracy with a smaller RMSE, suggesting its proficiency in capturing temporal dependencies. Conversely, SARIMA outperforms LSTM in Tuntungan, indicating its effectiveness in capturing seasonal and autoregressive components of the data. These findings underscore the importance of understanding regional variations and model-specific characteristics for improving predictive accuracy. Further investigation and refinement of the models, considering the unique dynamics of each region, could lead to enhanced forecasting capabilities in hydrological or environmental applications.

3.3.2. MAE

The MAE comparison graph is presented on an actual scale (mm), showcasing the performance of both LSTM and SARIMA models across the four locations. Notably, the highest MAE values are recorded in Belawan, with LSTM and SARIMA yielding 5.65 mm and 5.79 mm respectively. Conversely, the smallest MAE values are observed in Sampali, with LSTM achieving 2.95 mm and SARIMA outperforming with a mere 0.53 mm. Additionally, in Tuntungan, SARIMA demonstrates its superior performance with a notably low MAE compared to LSTM. This analysis highlights the varying efficacy of both models across different locations, emphasizing the importance of considering regional factors in rainfall prediction (Figure 3). Overall, SARIMA shows better performance than LSTM in three out of the four locations (Kualanamu, Belawan, and Tuntungan), demonstrating significantly lower forecasting errors. LSTM only performs better in Sampali. This analysis suggests that SARIMA generally provides more accurate forecasts than LSTM for the locations considered, with Tuntungan showing the most significant improvement when using SARIMA over LSTM.

https://doi.org/10.36596/jcse.v5i2.843

 e-ISSN 2721-0251

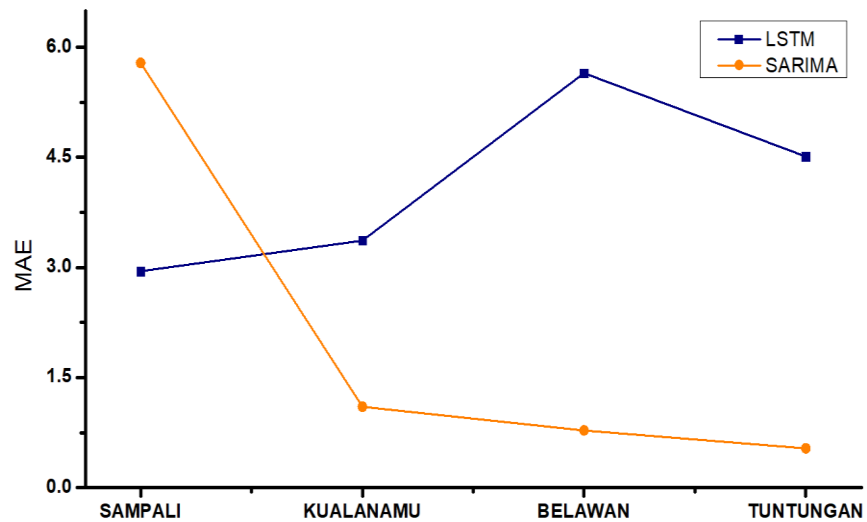

Figure 3. The MAE Comparison Graph Shows the MAE Values for LSTM and SARIMA Models Across Four Locations: Sampali, Kualanamu, Belawan, and Tuntungan.

3.3.3. Correlation Coefficient (r)

The correlation comparison graph is plotted on an actual scale (mm). The highest correlation values for both models are in Sampali, with values of 0.65 mm for LSTM and 0.56 mm for SARIMA in Belawan, and the smallest values are in Tuntungan, with 0.49 mm for LSTM and 0.47 mm for SARIMA in Kualanamu (Figure 4).

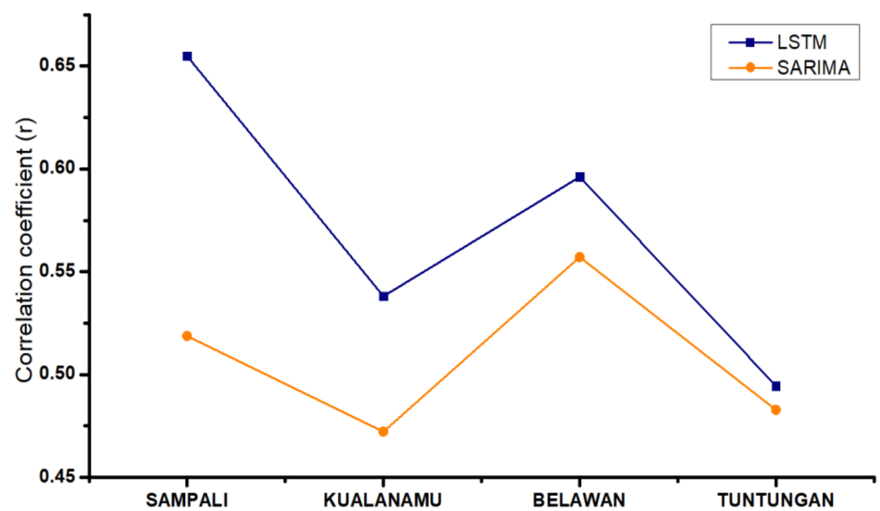

Figure 4. The Correlation Coefficient (r) Comparison Graph Shows the MAE Values for LSTM and SARIMA Models Across Four Locations: Sampali, Kualanamu, Belawan, and Tuntungan.

The correlation comparison graph, plotted on an actual scale (mm), provides insights into the relationship between predicted and actual rainfall values for both LSTM and SARIMA models across four locations. In Sampali, both models achieve their highest correlation values, with LSTM at 0.65 mm and SARIMA at 0.56 mm, indicating a strong relationship between predicted and observed values in this location. Conversely, in Belawan, the correlation values are notably lower, with SARIMA showing a correlation of 0.56 mm. The smallest correlation values are observed in Tuntungan for LSTM (0.49 mm) and in

https://doi.org/10.36596/jcse.v5i2.843

Kualanamu for SARIMA (0.47 mm), suggesting weaker predictive accuracy in these areas. Overall, the analysis reveals that while both models perform well in Sampali, their effectiveness varies in other locations, with SARIMA generally providing more stable and reliable predictions across the board except in areas where LSTM shows higher correlations. This highlights the importance of location-specific model selection for optimal rainfall prediction accuracy.

3.4 Temporal Pattern Analysis

Temporal Pattern Analysis for every location can be found below:

3.4.1. Sampali

In Sampali, there are differences in the values generated by the SARIMA model, which are quite different from the observed values, with only a few closely approaching the observed values. The graph in the LSTM (Long Short-Term Memory) method with monthly data shows two curves. The gray line (Observed) indicates the actual rainfall values with significant variations at some points. There are sharp peaks and drastic drops in this data. The blue line (LSTM) shows the prediction results from the LSTM model. These predictions tend to be smoother and follow the general trend of the observed data, although they do not always accurately capture all peaks and valleys. These results are obtained using a batch size of 64 with a correlation value of 0.65 for the LSTM model (Figure 5).

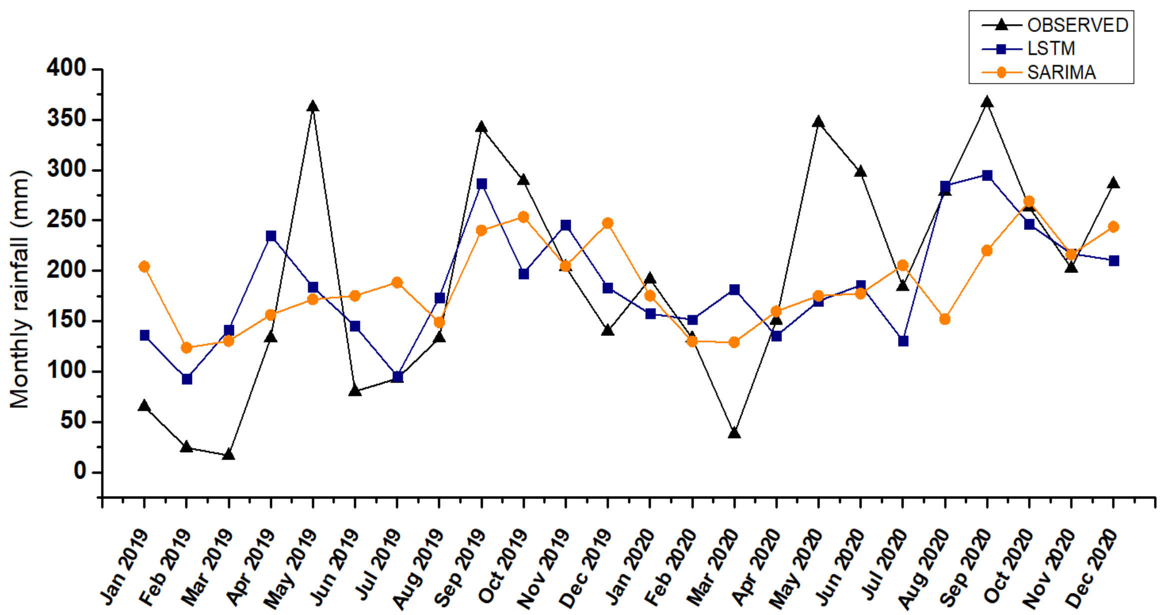

Figure 5. Temporal Patterns of Predicted Monthly Rainfall using SARIMA and LSTM Models Compared to Observed Data in Sampali from January 2019 to December 2020.

The provided graph compares the monthly rainfall from January 2019 to December 2020 as observed blue line) and predicted by two models: LSTM (Long Short-Term Memory, blue line) and SARIMA (Seasonal Autoregressive Integrated Moving Average, orange line). The observed rainfall data shows significant variability, with notable peaks around May 2019, August 2019, and September 2020. The LSTM model generally follows the observed trends but shows more fluctuations and is sometimes closer to the observed values. In contrast, the SARIMA model provides a smoother prediction, capturing the overall seasonal trends but missing some of the sharper peaks and troughs present in the observed data.

https://doi.org/10.36596/jcse.v5i2.843

 e-ISSN 2721-0251

Both models show a similar trend to the observed data but differ in their response to short-term fluctuations.

3.4.2. Kualanamu

The SARIMA model used in Kualanamu seems to provide a rough representation of the actual data, with weaknesses in capturing extreme changes. This may require parameter adjustments or other model approaches that can be more sensitive to sharp fluctuations in the data. Overall, the predictions generated by the LSTM model in Kualanamu follow the general trend of the observed data. The LSTM model is quite adept at capturing seasonal patterns and cycles in the data. Some major seasonal peaks and valleys are well followed, although the prediction amplitudes are often lower or higher than the actual data. These results are obtained using a batch size of 64 with a correlation value of 0.54 for the LSTM model (Figure 6).

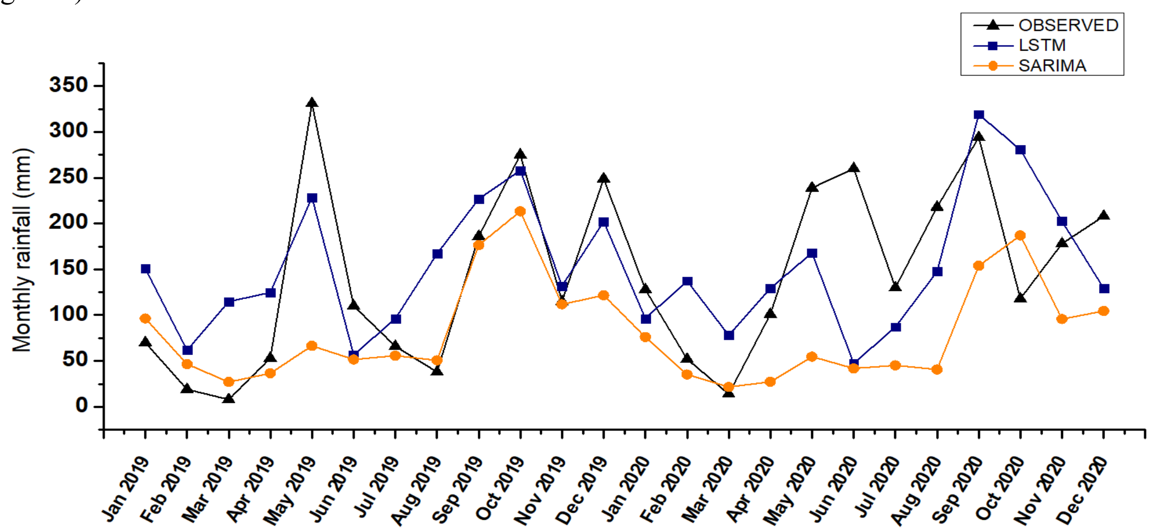

Figure 6. Temporal Patterns of Predicted Monthly Rainfall using SARIMA and LSTM Models Compared to Observed Data in Kulanamu from January 2019 to December 2020.

The graph presents a comparison of observed monthly rainfall (blue line) against predictions from LSTM (blue line) and SARIMA (orange line) models from January 2019 to December 2020. The observed rainfall data exhibits high variability with significant peaks around May 2019, September 2019, and September 2020. The LSTM model captures the general pattern of the observed rainfall, closely following the sharp increases and decreases, but sometimes exaggerates the magnitude of these fluctuations. Conversely, the SARIMA model provides a smoother prediction, successfully identifying the overall trend but often underestimating the magnitude of the rainfall peaks and failing to capture some short-term variations. Overall, while both models reflect the seasonal patterns of rainfall, the LSTM model is more responsive to sudden changes, whereas the SARIMA model offers a steadier, less variable forecast.

3.4.3. Belawan

In Belawan, the graph illustrates how the SARIMA model attempts to predict future values from time series data based on its historical patterns. Although this model's predictions are quite good at following the general trend, there are limitations in capturing extreme fluctuations, which are a common challenge in time series modeling. The orange line indicates predictions that tend to be smoother and follow the general trend of the observed data, although they do not accurately capture all peaks and valleys. On the

https://doi.org/10.36596/jcse.v5i2.843

other hand, the LSTM model demonstrates good capability in capturing the general trends and seasonal patterns of monthly rainfall data. Although it does not always accurately capture all peaks and valleys. These results are obtained using a batch size of 32 with a correlation value of 0.60 for the LSTM model (Figure 7).

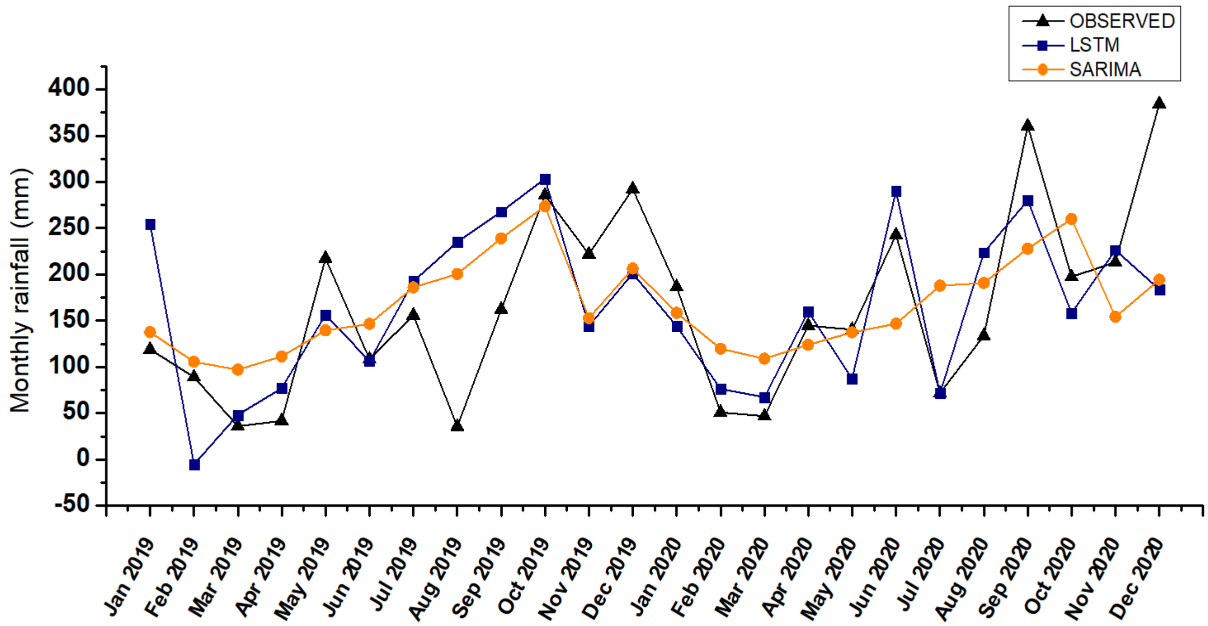

Figure 7. Temporal Patterns of Predicted Monthly Rainfall using SARIMA and LSTM Models Compared to Observed Data in Belawan from January 2019 to December 2020.

The graph depicts a comparative analysis of observed monthly rainfall (blue line) and the predictions generated by the LSTM (Long Short-Term Memory, blue line) and SARIMA (Seasonal Autoregressive Integrated Moving Average, orange line) models from January 2019 to December 2020. The observed data exhibits considerable fluctuations, with notable peaks in May 2019, September 2019, and December 2020. The LSTM model closely follows the observed data's trends and captures the peaks and troughs more accurately, though it sometimes overestimates the magnitude of rainfall. This indicates the LSTM model's strength in handling complex patterns and short-term variations. In contrast, the SARIMA model provides a smoother and more consistent prediction, effectively capturing the overall seasonal trend but often underestimating the intensity of rainfall peaks and missing some short-term variability. The SARIMA model's predictions are less volatile, offering a more stable but less detailed forecast. Therefore, while the LSTM model demonstrates better performance in tracking the rapid changes in rainfall, the SARIMA model excels in offering a generalized view of seasonal trends.

3.4.4. Tuntungan

The graph in Tuntungan appears to be less responsive to extreme fluctuations. For example, the high peaks around points 237-239 and sharp declines around point 241 are not fully reflected in the prediction line. The blue line (Observed) shows observed data with significant fluctuations at some points. There are several sharp peaks and drastic declines in this data. The orange line (Predicted) indicates the prediction results from the SARIMA model. These predictions tend to be smoother and do not always capture sharp peaks and valleys in the observed data. In contrast to the prediction data in the previous city, Tuntungan shows quite different results from the observational data, although there are still some

https://doi.org/10.36596/jcse.v5i2.843

 e-ISSN 2721-0251

points that approximate. In this city, there are still difficulties in predicting and capturing extreme fluctuations in the data. These results are obtained using a batch size of 64 with a correlation value of 0.49 for the LSTM model (Figure 8).

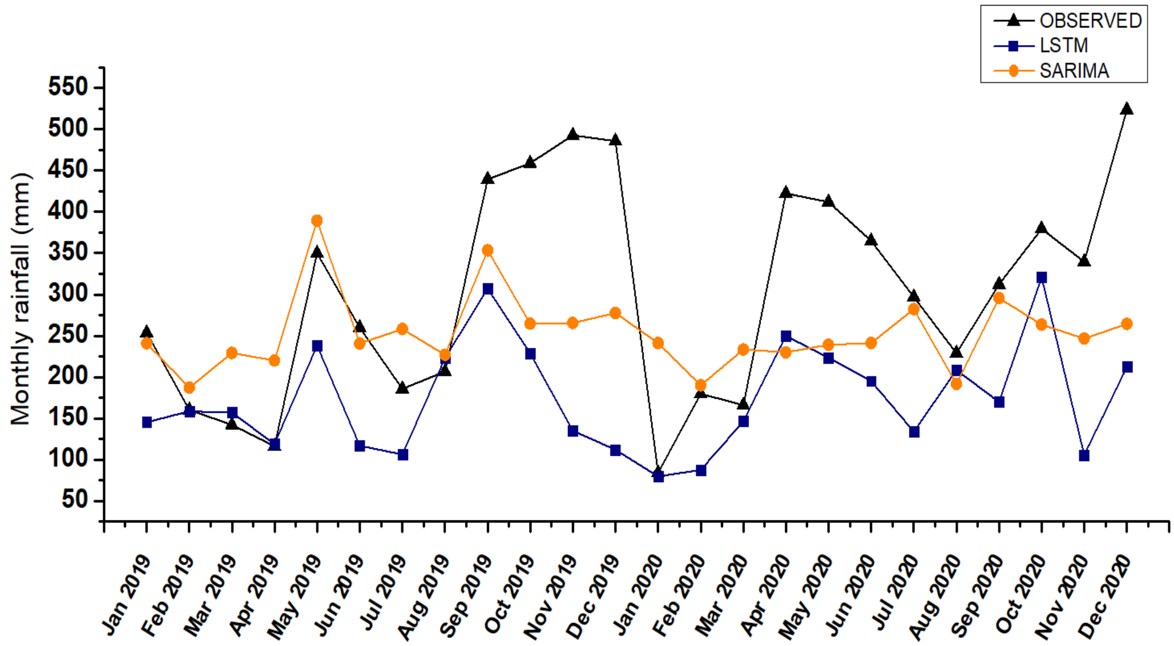

Figure 8. Temporal Patterns of Predicted Monthly Rainfall using SARIMA and LSTM Models Compared to Observed Data in Tuntungan from January 2019 to December 2020.

The graph displays monthly rainfall data from January 2019 to December 2020, comparing observed rainfall (blue line) with predictions from two models: LSTM (blue line) and SARIMA (orange line). The observed rainfall exhibits significant variability, with peaks around mid-2019, early 2020, and mid to late 2020. Both models attempt to capture this variability but differ in their performance. The LSTM model shows greater fluctuations and often fails to align closely with the observed data, particularly in capturing the higher peaks and some of the lower troughs. This suggests that while LSTM can model complex patterns, it struggles with the high variability and extreme values present in the observed rainfall data. The SARIMA model, on the other hand, demonstrates a more smoothed prediction, capturing some of the general trends but missing the sharper peaks and valleys. SARIMA's performance indicates a better fit for the general trend but less sensitivity to abrupt changes in rainfall. Overall, neither model perfectly replicates the observed data, but the SARIMA model appears to provide a more stable prediction, albeit at the cost of missing some of the finer details captured by the LSTM model. This analysis highlights the challenge of accurately modeling highly variable time series data like monthly rainfall.

The comparison results between the SARIMA and LSTM models across four locations are summarized in the Table 2. The evaluation metrics include Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Correlation Coefficient (r).

https://doi.org/10.36596/jcse.v5i2.843

Table 2. Comparison Result between the SARIMA and LSTM

Location	Metric	SARIMA	LSTM
Sampali	RMSE (mm)	15.67	14.45
	MAE (mm)	0.53	2.95
	Correlation (r)	0.56	0.63
Kualanamu	RMSE (mm)	18.45	19.30
	MAE (mm)	4.12	4.50
	Correlation (r)	0.47	0.54
Belawan	RMSE (mm)	28.36	27.68
	MAE (mm)	5.79	5.65
	Correlation (r)	0.56	0.60
Tuntungan	RMSE (mm)	2.61	3.10
	MAE (mm)	0.45	1.20
	Correlation (r)	0.49	0.49

To better understand the performance differences between SARIMA and LSTM models across the study locations, further analysis of spatial variability is essential. Each location's unique geographical and meteorological characteristics can significantly influence the prediction accuracy of these models. By examining the spatial variability, researchers can identify specific patterns and factors contributing to the models' strengths and weaknesses in different areas. This analysis can reveal the underlying reasons why certain models perform better in specific locations, aiding in the development of more tailored and effective predictive models. The practical implications of the performance differences between SARIMA and LSTM models are significant for field applications. For instance, areas where SARIMA shows higher accuracy may benefit from its use in operational settings, such as agricultural planning and water resource management, due to its ability to capture linear trends and seasonality. On the other hand, LSTM's superior performance in areas with complex, non-linear patterns suggests its suitability for applications requiring detailed temporal predictions, such as flood forecasting and climate change impact assessments. Understanding these implications helps stakeholders choose the most appropriate model for their specific needs, ensuring better decision-making and resource allocation.

4. Conclusion

The SARIMA and LSTM models both demonstrate distinct capabilities and limitations in predicting monthly rainfall data. SARIMA excels in capturing general trends and seasonal patterns, providing a reliable overview of data movement, but it struggles with accurately predicting extreme changes and sharp fluctuations, leading to misalignments during high peaks and low valleys. In contrast, the LSTM model shows a stronger ability to follow the general direction and seasonal patterns of the data, sometimes closely matching observed values. However, it also faces challenges in accurately predicting very sharp peaks and valleys. Enhancing LSTM's prediction accuracy could involve optimizing hyper parameters, adding more training data, or integrating additional methods to handle high variability in the data. Overall, while SARIMA offers stability in trend prediction, LSTM's flexibility makes it more adept at capturing complex patterns, though both require further refinement for precise rainfall forecasting.

Future model development should focus on integrating more advanced techniques and hybrid models that combine the strengths of both SARIMA and LSTM. For instance, incorporating external climate variables and satellite data could enhance the predictive accuracy of both models. Additionally, developing adaptive models that can automatically adjust parameters based on real-time data inputs may further improve the reliability of rainfall predictions. The findings of this study have significant

https://doi.org/10.36596/jcse.v5i2.843

implications for stakeholders in rainfall prediction applications. Accurate and reliable monthly rainfall forecasts are crucial for sectors such as agriculture, water resource management, disaster preparedness, and urban planning. By providing high-quality rainfall data, the models can help stakeholders make informed decisions, optimize resource management, and develop effective mitigation strategies to reduce the impact of hydro-meteorological disasters. Enhanced predictive capabilities also support long-term planning and climate adaptation efforts, ensuring resilience against future climatic challenges.

The study offers a comprehensive comparison of SARIMA and LSTM models, providing clear performance metrics and detailed methodology, which ensures replicability and helps in identifying the most suitable model for different regions. It provides region-specific insights, aiding local stakeholders in making informed decisions. However, the research faces limitations such as data availability and resolution, the complexity of LSTM models, a limited geographic scope, and potential overfitting issues. For future research, integrating SARIMA and LSTM into a hybrid model could enhance prediction accuracy by combining linear and non-linear modeling strengths. Expanding the study to more diverse regions, utilizing high-resolution data, and incorporating external variables like temperature and humidity can further improve predictions. Developing adaptive models that update in real-time and exploring other advanced machine learning techniques such as CNNs or attention-based mechanisms are also promising areas.

References

[1] E. S. Adiningsih, “Tinjauan Metode Deteksi Parameter Kekeringan Berbasis Data Penginderaan Jauh,” Pros. Semin. Nas. Penginderaan Jauh 2014, pp. 210–220, 2014. [Online]. Available: https://karya.brin.go.id/id/eprint/10889/.

[2] T. Dyah, P. Pinuji, and Ikhwanudin, “Mitigasi Bencana Pada Bencana Hidrometeorologi di Indonesia,” *Sci. Eng. Natl. Semin. 8 (SENS 8)*, vol. 8, no. 1, pp. 144–148, 2023, [Online]. Available: https://conference.upgris.ac.id/index.php/sens/article/view/4994

[3] D. Setiawan, “Analisis Curah Hujan di Indonesia untuk Memetakan Daerah Potensi Banjir dan Tanah Longsor dengan Metode Cluster Fuzzy C-Means dan Singular Value Decompotition (SVD),” *Eng. Math. Comput. Sci. J.*, vol. 3, no. 3, pp. 115–120, 2021, doi: 10.21512/emacsjournal.v3i3.7428.

[4] W. Rahmalina and Novreta, “Peramalan Indeks Kekeringan Kelayang Menggunakan Metode Sarima dan SPI,” *Potensi J. Sipil Politek.*, vol. 22, no. 1, pp. 64–75, 2020, doi: 10.35313/potensi.v22i1.1824.

[5] A. Rosyida, R. Nurmasari, S. Bnpb, K. Data Spasial BNPB, and K. Kunci, “Analisis Perbandingan Dampak Kejadian Bencana Hidrometeorologi Dan Geologi Di Indonesia Dilihat Dari Jumlah Korban Dan Kerusakan (Studi: Data Kejadian Bencana Indonesia 2018),” *J. Dialog Penanggulangan Bencana*, vol. 10, no. 1, pp. 12–21, 2019. [Online]. Available: https://perpustakaan.bnpb.go.id/jurnal/index.php/JDPB/article/view/127/97.

[6] A. Taufan Maulana and A. Andriansyah, “Mitigasi Bencana di Indonesia,” *COMSERVA J. Penelit. dan Pengabdi. Masy.*, vol. 3, no. 10, pp. 3996–4012, 2024, doi: 10.59141/comserva.v3i10.1213.

[7] S. Anwar, “Peramalan Suhu Udara Jangka Pendek di Kota Banda Aceh dengan Metode Autoregressive Integrated Moving Average (ARIMA),” *Malikussaleh J. Mech. Sci. Technol.*, vol. 5, no. 1, p. 6, 2017, doi: 10.29103/mjmst.v5i1.10882.

[8] L. J. Sinay, F. K. Lembang, S. N. Aulele, and D. Mustamu, “Analisis Curah Hujan Bulanan Di Kota Ambon Menggunakan Model Heteroskedastisitas: Sarima-Garch,” *Media Stat.*, vol. 13, no. 1, pp. 68–79, 2020, doi: 10.14710/medstat.13.1.68-79.

[9] S. J. and S. A., “A Comparative Analysis Of Web Information Extraction Techniques Deep Learning Vs. Naïve Bayes Vs. Back Propagation Neural Networks In Web Document Extraction,” *ICTACT J. Soft Comput.*, vol. 06, no. 02, pp. 1123–1129, 2016, doi: 10.21917/ijsc.2016.0156.

[10] M Devid Alam Carnegie and Chairani, “Perbandingan Long Short Term Memory (LSTM) dan Gated Recurrent Unit (GRU) Untuk Memprediksi Curah Hujan,” *J. Media Inform. Budidarma*, vol. 7, no. 3, pp. 1022–1032, 2023, doi: 10.30865/mib.v7i3.6213.

[11] D. Desmonda, T. Tursina, and M. A. Irwansyah, “Prediksi Besaran Curah Hujan Menggunakan Metode Fuzzy Time Series,” *J. Sist. dan Teknol. Inf.*, vol. 6, no. 4, p. 141, 2018, doi: 10.26418/justin.v6i4.27036.

https://doi.org/10.36596/jcse.v5i2.843

[12] M. R. Pahlevi, “Prediksi Harga Forex Menggunakan Algoritma Long Short-Term Memory,” *Jnanaloka*, pp. 69–76, 2023, doi: 10.36802/jnanaloka.2022.v3-no2-69-76.
[13] A. M. Soetamto dan Ulfah, *Metode ARIMA, Modul Pelatihan Peningkatan Akurasi Prakiraan Musim*. Jakarta: Badan Meteorologi dan Geofisika, 2006.
[14] A. Parasyris, G. Alexandrakis, G. V. Kozyrakis, K. Spanoudaki, and N. A. Kampanis, “Predicting Meteorological Variables on Local Level with SARIMA, LSTM and Hybrid Techniques,” *Atmosphere (Basel).*, vol. 13, no. 6, 2022, doi: 10.3390/atmos13060878.
[15] U. M. Sirisha, M. C. Belavagi, and G. Attigeri, “Profit Prediction Using ARIMA, SARIMA and LSTM Models in Time Series Forecasting: A Comparison,” *IEEE Access*, vol. 10, no. December, pp. 124715–124727, 2022, doi: 10.1109/ACCESS.2022.3224938.
[16] D. Wahyudi and I. V. Paputungan, “Pemodelan Curah Hujan Pada Kota Bengkulu Menggunakan Seasonal Autoregressive Integrated Moving Average (Sarima),” *Automata*, vol. 3, no. 2, 2022, [Online]. Available: https://journal.uii.ac.id/AUTOMATA/article/view/24319.
[17] R. F. Firdaus, “Prediksi Curah Hujan Menggunakan Metode Long Short Term Memory (Studi Kasus: Kota Bandung),” M.S. thesis, Dept. Informatics Engineering, Univ. Islam Indonesia, Yogyakarta, Indonesia, Oct. 2022. [Online]. Available: https://dspace.uii.ac.id/handle/123456789/42746.
[18] T. A. Faisal Muhammad and M. I. Irawan, “Implementasi Long Short-Term Memory (LSTM) untuk Prediksi Intensitas Curah Hujan (Studi Kasus: Kabupaten Malang),” *J. Sains dan Seni ITS*, vol. 12, no. 1, 2023, doi: 10.12962/j23373520.v12i1.106892.
[19] T. Lattifia, P. Wira Buana, and N. K. D. Rusjayanthi, “Model Prediksi Cuaca Menggunakan Metode LSTM,” *JITTER J. Ilm. Teknol. dan Komput.*, vol. 3, no. 1, pp. 994–1000, 2022. [Online]. Available: https://www.neliti.com/publications/431686/model-prediksi-cuaca-menggunakan-metode-lstm..
[20] M. Rizki, S. Basuki, and Y. Azhar, “Implementasi Deep Learning Menggunakan Arsitektur Long Short Term Memory(LSTM) Untuk Prediksi Curah Hujan Kota Malang,” *J. Repos.*, vol. 2, no. 3, pp. 331–338, 2020, doi: 10.22219/repositor.v2i3.470.
[21] S. Hochreiter and J. Schmidhuber, “Long Short-Term Memory,” Neural Computation, vol. 9, no. 8. MIT Press, pp. 1735–1780, Nov. 01, 1997. doi: 10.1162/neco.1997.9.8.1735.
[22] J. S. Armstrong, “Evaluating Forecasting Methods,” pp. 443–472, 2001, doi: 10.1007/978-0-306-47630-3_20.
[23] D. Perdana and A. Muklason, “Machine Learning untuk Peramalan Kualitas Indeks Standar Pencemar Udara DKI Jakarta dengan Metode Hibrid ARIMAX-LSTM,” *Ilk. J. Comput. Sci. Appl. Informatics*, vol. 5, no. 3, pp. 209–222, 2023, doi: 10.28926/ilkomnika.v5i3.588.
[24] M. Yusuf, A. Setyanto, and K. Aryasa, “Analisis Prediksi Curah Hujan Bulanan Wilayah Kota Sorong Menggunakan Metode Multiple Regression,” *J. Sains Komput. Inform. (J-SAKTI*, vol. 6, no. 1, pp. 405–417, 2022. doi: 10.30645/j-sakti.v6i1.455.
[25] A. A. Suryanto, “Penerapan Metode Mean Absolute Error (Mea) Dalam Algoritma Regresi Linear Untuk Prediksi Produksi Padi,” *Saintekbu*, vol. 11, no. 1, pp. 78–83, 2019, doi: 10.32764/saintekbu.v11i1.298.
[26] Hilda Nurfaidah and Wahyuni Abidin, “Penerapan Metode Single Moving Average Dalam Peramalan Curah Hujan Kota Makassar,” *J. MSA (Mat. dan Stat. serta Apl.*, vol. 11, no. 2, pp. 134–139, 2024, doi: 10.24252/msa.v11i2.45815.
[27] R. M. Putra *et al.*, “Prediksi Harian Suhu Udara Permukaan dengan Jaringan Syaraf Tiruan : Studi Kasus di Kawasan perkotaan dan Pesisir Jakarta, Indonesia,” *Bul. GAW Bariri*, vol. 4, no. 1, pp. 31–38, 2023, doi: 10.31172/bgb.v4i1.84.
[28] S. C. Kafle and E. Hooda, “ARIMA and Exponential Smoothing Model to Forecast Average Annual Precipitation in Bharatpur, Nepal,” BMC Journal of Scientific Research, vol. 6, no. 1. Nepal Journals Online (JOL), pp. 113–125, Dec. 22, 2023. doi: 10.3126/bmcjsr.v6i1.60959.
[29] R. M. Putra and N. Anjar Rani, “Prediksi Curah Hujan Harian di Stasiun Meteorologi Kemayoran Menggunakan Artificial Neural Network (ANN),” *Bul. GAW Bariri*, vol. 1, no. 2, pp. 101–108, 2020, doi: 10.31172/bgb.v1i2.35.